

Off-line smoothing

1-sliced

$$\begin{aligned} p(z_t = h | x_{1:T}) &\propto p(z_t = h, x_{1:T}) \\ &= p(x_{1:t-1}, z_t = h) p(x_{t:T} | z_t = h) \\ &= \underbrace{p(z_t = h)}_{\hat{p}_t(h)} p(x_t | z_t = h) p(x_{t+1:T} | z_t = h) \\ &= \hat{p}_t(h) p(x_t | z_t = h) b_t(h) \end{aligned}$$

2-sliced

$$\begin{aligned} p(z_t = h, z_{t+1} = h' | x_{1:T}) &\propto p(z_t = h, z_{t+1} = h', x_{1:T}) \\ &= p(x_{1:t-1}, z_t = h) p(x_t | z_t = h) p(z_{t+1} = h', x_{t+1:T} | z_t = h) \\ &= \hat{p}_t(h) p(x_t | z_t = h) p(z_{t+1} = h' | z_t = h) \underbrace{b_{t+1}(h')}_{b_{t+1}(h')} p(x_{t+1:T} | z_{t+1} = h') \end{aligned}$$

Sampling states

$$p(z_{1:T+1} | x_{1:T})$$

$$= p(z_1 | x_{1:T}) p(z_{2:T+1} | z_1, x_{2:T})$$

$$= p(z_1 | x_{1:T}) p(z_2 | z_1, x_{2:T}) p(z_{3:T+1} | z_2, x_{3:T})$$

$$= p(z_1 | x_{1:T}) \left[ \prod_{t=1}^{T-1} p(z_t | z_{t-1}, x_{t:T}) \right] p(z_{T+1} | z_T)$$

$$p(z_1=h | x_{1:T}) \propto p(z_1=h, x_{1:T})$$

$$= p(z_1=h, x_1) p(x_{2:T} | z_1=h)$$

$$= p(z_1=h) p(x_1 | z_1=h) b_1(h)$$

$$p(z_t=h | z_{t-1}, x_{t:T}) \propto p(z_t=h, x_{t:T} | z_{t-1})$$

$$= p(z_t=h, x_t | z_{t-1}) p(x_{t+1:T} | z_t=h)$$

$$= p(z_t=h | z_{t-1}) p(x_t | z_t=h) b_t(h)$$

# GMM

$\theta'$  all param.  $\theta'_1, \dots, \theta'_C$  and  $\pi'$

Complete data  $D = (z_1, x_1), \dots, (z_N, x_N)$

$$L(\theta'; D) = \prod_{n=1}^N \pi'_{z_n} p(x_n | \theta'_{z_n})$$

Ind. func  
↓

$$= \prod_n \prod_{c=1}^C [\pi'_c p(x_n | \theta'_c)]^{I(c=z_n)}$$

$$\ell(\theta'; D) = \sum_n \sum_c I(c=z_n) [\log \pi'_c + \log p(x_n | \theta'_c)]$$

$$= \sum_c \underbrace{\left[ \sum_n I(c=z_n) \right]}_{N_c} \log \pi'_c + \sum_c \underbrace{\sum_n I(c=z_n) \log p(x_n | \theta'_c)}_{\sum_{n: z_n=c} \log p(x_n | \theta'_c)}$$

First term max by  $\pi'_c = N_c / N$

## EM for GMM

Parameters  $\theta = (\pi_1, \dots, \pi_c, \theta_1, \dots, \theta_c)$  where  $\theta_c = (\mu_c, \sigma_c^2)$ .

Current parameters  $\theta^i$ :

Expected complete log-likelihood

$$\sum_n E_{p(z_n | x_n, \theta^i)} [\ell(\theta; z_n, x_n)]$$

$$= \sum E \left[ \log \prod_c (\pi_c p(x_n | z_n=c, \theta_c))^{I(z_n=c)} \right]$$

$$= \sum E \left[ \sum_c I(z_n=c) \log \pi_c + \sum_c I(z_n=c) \log p(x_n | \theta_c) \right]$$

$$= \sum_{n,c} \underbrace{E[I(z_n=c)]}_{= p(z_n=c | x_n, \theta^i) = r_{nc}} \log \pi_c + \sum_{n,c} \underbrace{E[I(z_n=c)]}_{= r_{nc}} \log p(x_n | \theta_c)$$

$$= \sum_c \underbrace{\left[ \sum_n r_{nc} \right]}_{(A)} \log \pi_c + \sum_c \underbrace{\sum_n r_{nc} \log p(x_n | \theta_c)}_{(B_c)}$$

(A) and each (B<sub>c</sub>) can be maximised separately.

(A) max. by

$$\pi_c = \sum_n r_{nc} / N = \overset{\text{def as } \sum_n r_{nc}}{r_c} / N$$

For (B<sub>c</sub>),

$$\text{let } \alpha_c = \frac{1}{\sigma_c}$$

and

$$\begin{aligned} \ell_c(\mu_c, \alpha_c) &= \sum_n r_{nc} \log \left[ \frac{\alpha_c}{\sqrt{2\pi}} e^{-\frac{\alpha_c^2}{2}(x_n - \mu_c)^2} \right] \\ &= \sum_n r_{nc} \log \alpha_c - \sum_n r_{nc} \frac{\alpha_c^2}{2} (x_n - \mu_c)^2 + C \end{aligned}$$

$\nearrow$  some const.

$$\frac{d\ell}{d\mu_c} = \sum_n r_{nc} \alpha_c^2 (x_n - \mu_c) \quad \text{and}$$

$$\frac{d\ell}{d\mu_c} = 0 \Rightarrow \sum_n r_{nc} \cancel{\alpha_c^2} x_n = \sum_n r_{nc} \cancel{\alpha_c^2} \mu_c$$

$$\text{so} \quad \mu_c = \frac{\sum_n x_n r_{nc}}{r_c}$$

—

$$\frac{d\ell}{d\alpha} = \sum_n \frac{r_{nc}}{\alpha_c} - r_{nc} \alpha_c (x_n - \mu_c)^2$$

$$\frac{d\ell}{d\alpha} = 0 \Rightarrow \frac{1}{\alpha_c} \sum_n r_{nc} = \alpha_c \sum_n r_{nc} (x_n - \mu_c)^2$$

$$\text{so} \quad \sigma^2 = \frac{1}{\alpha^2} = \frac{\sum_n r_{nc} (x_n - \mu_c)^2}{r_c}$$